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Academic Ranking Scales in Economics: Prediction and Imputation

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Academic Ranking Scales in Economics: Prediction and Imputation *†

Alona Zharova‡, Andrija Mihoci§ and Wolfgang Karl Härdle¶

Abstract

We address the problem that often hampers decision making in academic institutions – incomplete research profiles. We suggest a framework for collating ranking data of scientists for comparison purposes. As the result of an analysis of the interconnectedness between HB sub-rankings through quantile regression, we propose a HB common score for scholars within the HB community. The cross-ranking dependence analysis of Handelsblatt, Research Papers in Economics and Google Scholar ranking schemes shows that researcher age and field of specialization – mapped onto the JEL classification codes – have a substantial impact on the resulting scores.

JEL classification: C81, C53, C21, M10

Keywords: ranking, prediction, quantile regression, Handelsblatt, RePEc, Google Scholar

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*Version 2.

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1 Introduction

Publication in academic and professional journals is a vital aspect of any scientist's career. The number of media outlets and the quality of published research influences decisions on jobs, salary, tenure and so on. Academic ranking scales, particularly in economics, are commonly used for the classification, judgment and evaluation of the scientific depth of individual research. These ranking systems all compete against each other and allow for different disciplinary gravity to be applied. They try to provide a fair platform for the evaluation of research results at universities, research centers and institutes, interdisciplinary groups, etc.

Ranking systems also play a key role in performance comparison and the clarification of individual contribution to the overall ranking of an institution. For instance, decisions made during recruitment processes at German universities (in economic fields) are typically supported by HB rankings, see Schläpfer and Schneider (2010). Furthermore, the distribution of financial resources at universities is often based on performance-related schemes that include achieved research results being taken into consideration, see Oberschelp and Jaeger (2010).

Our work deals with the performance analysis of researcher' profiles utilizing ranking observations from the most popular ranking systems in the economic and business sciences among German-speaking countries (Germany, Austria and Switzerland): Handelsblatt (HB), Research Papers in Economics (RePEc, here RP) and Google Scholar (GS) databases. The underlying ideas of these rankings and their comparison is discussed in Butz and Wohlrabe (2016), Wohlrabe (2011), Dilger and Müller (2011). We furthermore propose a framework for imputing rankings' data for comparison purposes, as decision-making is often accompanied by incomplete research profiles.

The research questions include: (i) How HB profiles of researchers can be completed based on the available data of the given HB sub-rankings? (ii) How to impute scores and how to predict an academic rank for researchers, who are not already included in a particular HB sub-ranking system? (iii) How strong is the cross-ranking dependence between the score outputs of HB, RP and GS? (iv) Which variables contribute significantly to ranking's dependence and score results?

Quantile regression offers a more detailed modelling framework than ordinary least-squares or least-absolute deviation fitting. The latter methods model the average response; a comprehensive ranking analysis of researchers should instead focus on other data characteristics, such as quantiles in our case. Quantile regression presently receives relatively close attention from the research community, along with the often used, average-response methods in ranking (citation) analysis employed by e.g. Hamermesh (2015). A comprehensive introduction to the quantile regression method is given in Koenker (2005). The rapidly growing literature shows a variety of approaches and applications in statistics and bibliometrics. Birks et al. (2014) use quantile regression with bootstrapped standard errors to predict the median, the 90^{th} and 95^{th} quantiles of the *h*-index for researchers in the health care field. For example, quantile regression allows: Rauber and Ursprung (2008) to investigate the research productivity of German academic economists over their life cycles; Kelchtermans and Veugelers (2011) to explore the research performance in relation to different sets of productivity drivers; whereas Stegehuis et al. (2015) predict the number of citations in publications. Here, in this study, we employ quantile regression to complete and define the research profiles of scholars.

Based on the conducted analyses, we show that quantile regression successfully interpolates and estimates the proposed HB common score. Academic rankings data exhibit different correlation structures over the underlying scores of HB, RP and GS, whereas the academic ranking variation has been documented to be quite sensitive to age differences. For example, the rank of both younger and older scientists is changing marginally (increasing) and is becoming more significant than the rank of middle-aged researchers. The scientists specializing in microeconomics (HB), international economics (RP) and general economics (GS) are associated with the respective leading positions. However, researchers from mathematical and quantitative fields occupy high positions across all three ranking systems.

The proposed approach and the findings of this research can be successfully used in practice (a) by selection committees in recruitment processes at universities (economic fields), (b) as a unique tool in decision making related to the allocation of research funds, (c) for collaborative purposes and grant proposal applications, etc. Our estimated HB common score can finally and confidently be used for a simultaneous comparison of candidates profiles from business (BWL) and economic (VWL) sciences.

The paper is structured as follows. The description of the analysed ranking systems and our data sources is presented in Section 2. Section 3 describes the statistical modelling steps related to data selection and the implementation of the predicting techniques. Section 4 discusses the HB, RP and GS comparison results and provides evidence on the impact of age and the research fields on ranking performance. Finally, Section 5 concludes.

2 Academic Ranking Systems

In this analysis, the terms *ranking*, *rank* and *score* are repeatedly used. Ranking represents the academic system or scale; rank denotes the position of each individual within the ranking; and score denotes the number of points assigned. Our statistical analysis is performed using R and MATLAB programming codes, available on the web-based repository hosting service and collaboration platform GitHub (accessed 02 Mar 2017) as well as QuantNet (accessed 02 Mar 2017).

2.1 Handelsblatt

The HB ranking provides a list of the most active researchers publishing in business and economics in Germany, Austria and Switzerland and also German-speaking researchers outside of these countries. The rankings were developed by the Konjunkturforschungsstelle (KOF) of the ETH Zürich on behalf of HB and German Association for Social Policy (Verein für Sozialpolitik). For this purpose the publication data from several external databases and the data from the Forschungsmonitoring (accessed 14 Oct 2015) are used. The HB ranking system has an established reputation among German-speaking economists since it influences decision making regarding the distribution of funds, recruitment process and performance evaluations at universities, Schläpfer (2011).

Moreover, HB produces and publishes a journal ranking list compiled from selected journals indexed in The American Economic Association's electronic bibliography (EconLit), see Combes and Linnemer (2010). Every journal from the HB list receives a weight of between 0.05 and 1, where a higher weight indicates a higher rank. An individual researcher's rank is generated from the number of weighted publications in relevant journals divided by the number of co-authors.

HB considers two fields: business sciences (BWL) and economics sciences (VWL). Within each field the following sub-rankings can be found: the Researcher Life's Work (LW); Current Researchers (CR); and Researchers Under 40 (U40). This gives a total of six BWL and VWL sub-rankings that are usually published every 24 months. The CR ranking is based on researchers' publications in predetermined journals over the last five years, whereas the U40 ranking considers all scientists younger than 40. The LW ranking, finally, takes all rated publications from the HB journals' list into account. It is worth noting that each researcher is present in either the VWL or in the BWL ranking, although inside each category, the individual can belong to any of the sub-ranking categories, LW, CR or U40 (the last only if he/she is younger than 40).

Here we utilize the sub-rankings of 250 individuals from VWL LW in 2015 and 250 individuals from BWL LW in 2014. For the sake of brevity, we provide a detailed descriptive analysis with programming codes in GitHub (accessed 02 Mar 2017); the results are available from the author upon request. In order to implement the analyses of the research fields and the age of the researchers based on the score, we have had to eliminate the individuals with missing observations, i.e. with no information on age or research fields.

2.2 Research Papers in Economics

The RP ranking system collects the bibliographic data of journal articles, books, working papers and other scientific media outlets. It contains around 2.3 million research items from more than 2,800 journals and 4,500 working paper series, see RePEc (accessed 02 Mar 2017). Although the RP project offers a broad spectrum of services, in this paper we focus solely on author ranking.

The main idea of the RP author's ranking system is to publish a list of the top 5% researchers on a monthly basis, from a pool of 50,000 registered individuals, based on an average rank score. This score is calculated based on a two-step procedure for each author. First, the authors are individually ranked within each of the 36 separate sub-rankings, excluding the w-index, a special case of the h-index. Second, a harmonic mean of the individual ranks represents this average rank score. In contrast to HB and GS, one should note that within the RP system the top-ranked scientists receive the lowest score and vice versa. For more details, we refer to Zimmermann (2013) and the corresponding RP webpage.

Contrary to HB, all RP sub-rankings receive the same weight while providing the average rank score, although they may impose a weighting scheme. To boost an HB score, for instance, an author must consider the journal ranking list, whereas to improve their RP score, researchers must consider other publication aspects, such as number of citations, abstract views, etc. Since the HB ranks were collected up to 2015 inclusive, the RP data for 2,304 individuals were collected for December 2015 (see Table 5 in Appendix).

2.3 Google Scholar

Contrary to HB and RP, GS concentrates on citation data (Hamermesh 2015). For every researcher, GS provides information about the number of citations per paper, the total number of citations, and the values of the h-index and the $i10$-index. The latest three indicators are here analyzed for 1,438 researchers. While calculating its metrics, GS takes into account all types of research publications. GS has good coverage in social sciences, economics, finance and business administration, see Harzing and Wal (2008), which makes it a desirable choice for our research purposes.

2.4 Data

Our paper considers HB (2014, 2015), RP (December 2015) and GS data (December 2015). In order to take into account both economic and business sciences, we select two main HB rankings with data available for 500 scientists: (i) the VWL LW in 2015 for 250 individuals and (ii) BWL LW in 2014 for 250 individuals. In December 2015, 2,304 researchers were listed in RP top 5% author ranking. Of those, 1,027 had a GS profile with corresponding GS scores.

A more detailed view of the data merging results is depicted in the mosaic plot, Figure 1. Consider the 500 scientists in HB. There are 122 individuals that also have an RP score, but not a GS profile. Similarly, 260 individuals have HB and GS scores, but no RP ranking data. Finally, there are 84 researchers (76 VWL, 8 BWL) for which the HB, RP and GS data are all available.

3 Methodology

Quantile regression offers a more comprehensive description of the relationship between two variables than a linear regression model. A linear regression model considers the re-

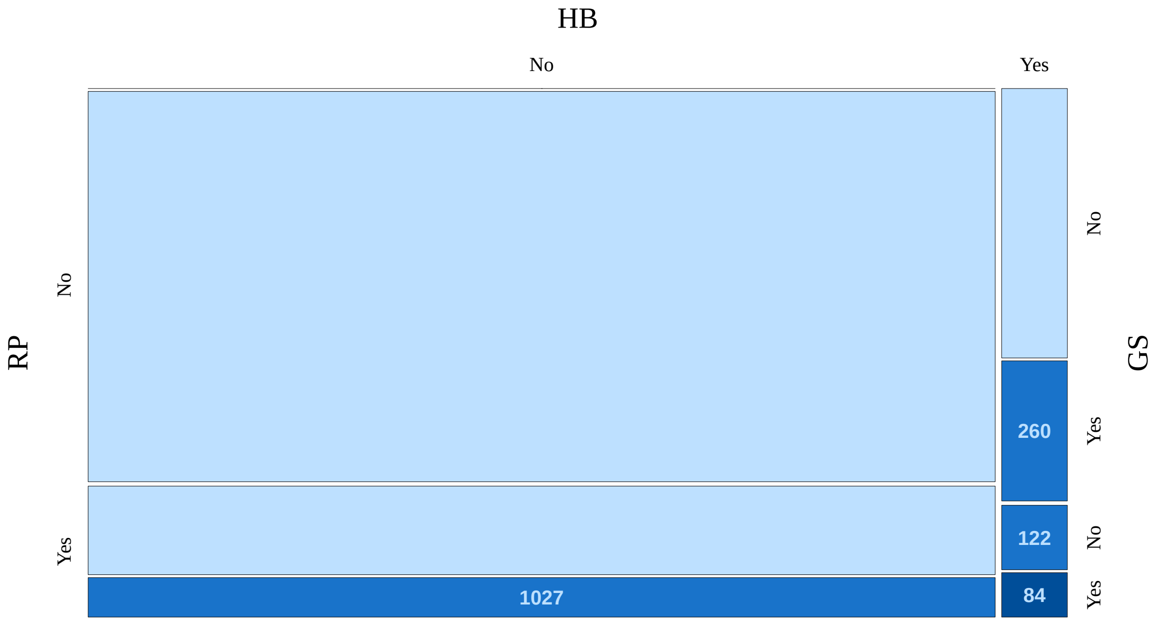

Figure 1: Mosaic plot for the number of researchers, whether merging of HB, RP and GS rankings takes place or not (Yes/No). The number of GS profiles is quite large and here they are only shown as an approximation. QARRmosage

lation between the dependent variable and one or more regressors as an average through the conditional mean function. On the contrary, quantile regression offers a broader perspective, since it models various conditional quantile functions, providing the possibility to depict the interconnections at various points, see Koenker (2015) and Baum (2013). For instance, for $\tau = 0.5$ the conditional median function results in a functional that is of limited influence, i.e. robust with respect to outliers. The analysis of data with thick tails and/or non-normal errors may not only turn out to be challenging but may also be biased for the linear model.

3.1 Quantile Regression

A linear regression (LR) model

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i, \;\; i = 1, \ldots, n, \tag{1}$$

where β_0 denotes the intercept and β_1 depicts the regression line slope with ε_i denoting the error term models the mean response of variable Y in relation to the regressor X. Here n stands for the sample size, i.e. in our case the number of data (ranking score) pairs $\{y_i, x_i\}_{i=1}^{n}$. As proposed by Koenker and Bassett (1978) and Koenker and Hallock (2001), we use the quantile regression (QR) model related to the linear regression (1) as

$$y_i = \beta_{0,\tau} + \beta_{1,\tau} x_i + \varepsilon_i, \; i = 1, \ldots, n, \tag{2}$$

where $\tau \in (0, 1)$ denotes the quantile level and the error ε_i has τ-quantile zero. For instance, setting $\tau = 0.5$ results in median quantile regression.

In the estimation of the linear regression model, the estimates of the unknown intercept and the slope parameter are found by least square minimization

$$\left(\widehat{\beta}_0, \widehat{\beta}_1\right) = \arg\min_{\beta_0, \beta_1} \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i)^2, \tag{3}$$

whereas in quantile regression by the minimization of the asymmetrically weighted residuals

$$\left(\widehat{\beta}_{0,\tau}, \widehat{\beta}_{1,\tau}\right) = \arg\min_{\beta_0, \beta_1} \sum_{i=1}^{n} \rho_\tau \left(y_i - \beta_0 - \beta_1 x_i\right), \tag{4}$$

with check function $\rho_\tau(u) = u\{\tau - \mathbf{I}(u < 0)\}$, where $\mathbf{I}(\cdot)$ denotes the indicator function.

3.2 HB Common Score

As a practical application of quantile regression for completing of research profiles, our study considers the prediction of HB sub-ranking scores. As there are more VWL researchers (76 individuals) relative to BWL (8 individuals) within the merged dataset (see Figure 11), we found it convenient to consider the score of a VWL researcher as the dependent variable and the score of the BWL researcher as the explanatory variable.

The resulting *HB common score*, thus, represents the observed and the predicted VWL scores. Consider the 250 VWL LW (y_i), as well as the 250 BWL LW (x_i) scores and then fit the (median) quantile regression (4). Denote the estimated model parameters by $\widehat{\beta}_{0,0.5}$ and $\widehat{\beta}_{1,0.5}$. Then the estimated HB common scores for the BWL researchers, using the analysed $n = 250$ pairs (y_i, x_i), are found by

$$\widehat{y}_i = \widehat{\beta}_{0,0.5} + \widehat{\beta}_{1,0.5} x_i, \quad i = 1, \ldots, 250. \tag{5}$$

Empirical results show an excellent explanatory performance, see e.g. the scatterplot with imposed fitted median quantile regression line and the Quantile-Quantile (QQ) plot in Figure 2, the estimated parameters in Table 1, and the goodness-of-fit measures in Table 2. The proposed HB common score is represented either by the existing VWL LW score for the VWL researchers or by the predicted score for the BWL researchers. In total, 500 HB common scores are associated with the 500 researchers.

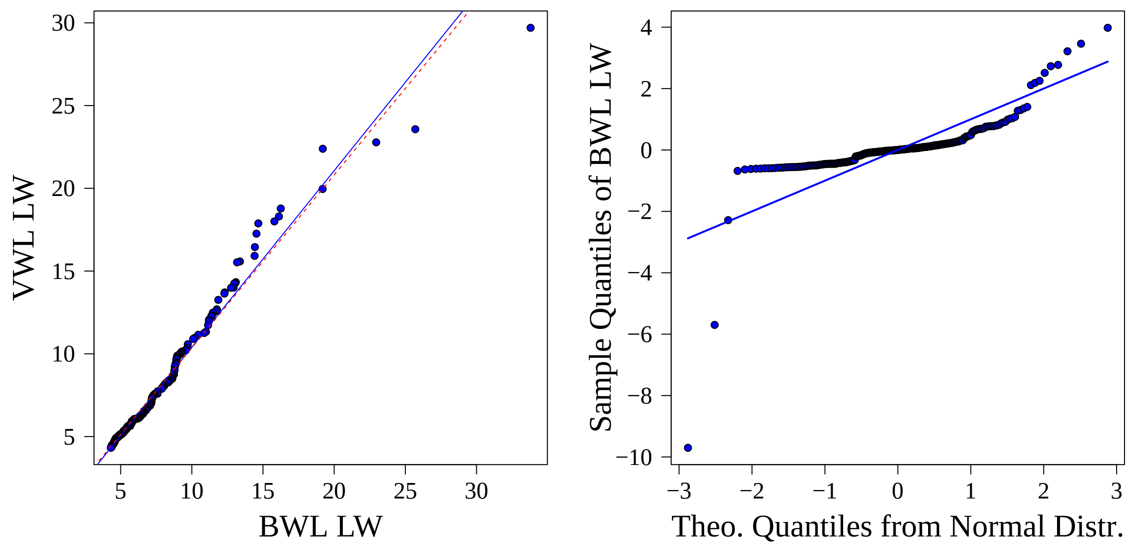

Figure 2: Scatterplot and quantile regression fit (left) of the HB on VWL LW vs BWL LW for a sample of 250 researchers within these rankings. Superimposed on the plot is the 0.50 quantile regression line (solid blue) and the least squares estimate of the conditional mean function (dashed red line). The coefficient of determination of the median regression equals 0.93. On the right, a QQ plot of the same sample of data versus a normal distribution.

		Est.	SE	t	p-value
BWL LW	$\widehat{\beta}_{1,0.5}$	-0.28	0.21	-1.37	0.1725
	$\widehat{\beta}_{0,0.5}$	1.07	0.04	27.71	0.0000

Table 1: Estimated regression model parameters (Est.) for rankings between VWL LW (dependent variable) and BWL LW (explanatory variable) for HB researchers. We provide the standard error of estimates (SE), the t-statistics to test whether the null hypothesis' the true parameter equals 0, and also the associated p-value.

	MSE	r^2
BWL LW	0.9976	0.9308

Table 2: Mean squared error (MSE) and coefficient of determination of the regression model for rankings between VWL LW (dependent variable) and BWL LW (explanatory variable) for HB researchers.

3.3 Quantile Levels

Outliers and extreme values may affect the regression estimation results. Here we first illustrate the robustness of quantile (median) regression to the presence of extreme values as compared with the ordinary least squares regression. We then study the structural HB score dependence and provide evidence for ranking prediction while changing the underlying quantile level.

In our modelling framework we now consider the data matrix excluding k (largest) observations. For convenience, we select $k \in \{1, 2, 5, 10, 15\}$ and present the resulting parameter estimates for the quantile (median) and linear regression in Table 3.

	$k = 0$	$k = 1$	$k = 2$	$k = 5$	$k = 10$	$k = 15$
$\widehat{\beta}_0$	-0.09	-0.50	-0.74	-0.91	-0.72	-0.57
$\widehat{\beta}_1$	1.05	1.10	1.14	1.17	1.14	1.11
$\widehat{\beta}_{0,0.5}$	-0.28	-0.54	-0.59	-0.63	-0.42	-0.21
$\widehat{\beta}_{1,0.5}$	1.07	1.12	1.12	1.13	1.09	1.05

Table 3: Estimated parameters using least squares and quantile regression ($\tau = 0.50$) for datasets excluding k largest observations/outliers.

One observes that the estimated quantile regression parameters are more insensitive to the presence of outliers. A relatively lower parameter estimates variability favours the quantile regression as compared to least squares fitting. In practice, our proposed ranking imputation framework is thus a preferable choice.

The presented framework provides an insight into the tail dependence structure of the HB score distribution. In this aspect we consider various quantile levels, namely

$$\tau = \{0.05, 0.25, 0.50, 0.75, 0.95\}.$$

Based on the ranking (BWL) data, one can estimate the corresponding quantiles of the other (VWL) observations, see the results of the employed quantile regression models in Figure 3. For example, consider a (top) rated BWL scientist with score 20. The predicted 95^{th} quantile VWL score is near 24, whereas the estimated 5^{th} quantile is close to 18.

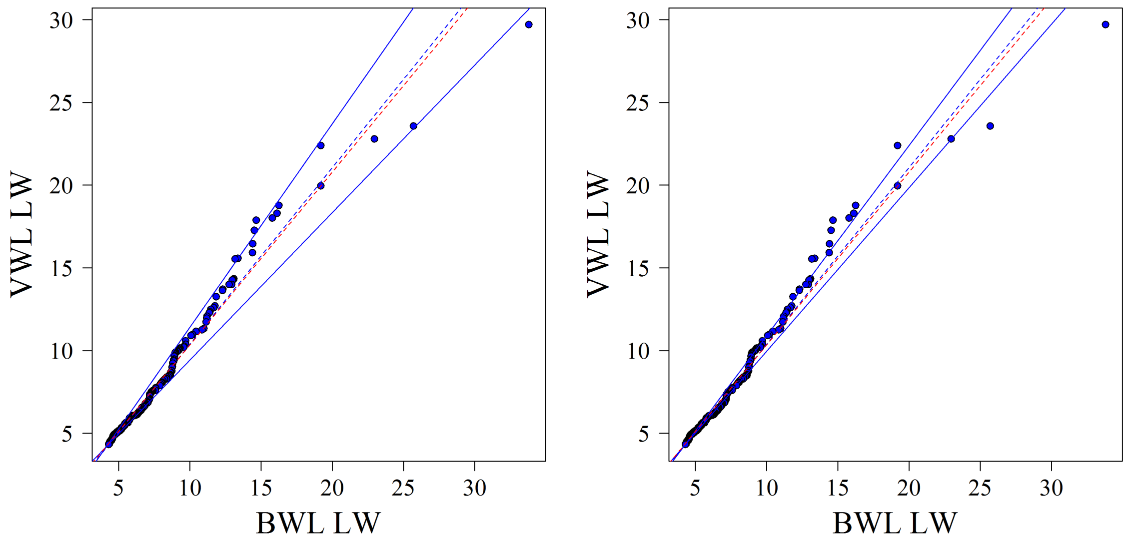

Figure 3: Scatterplot and Quantile Regression Fit of the HB on VWL LW vs. BWL LW for a sample of 250 researchers within these rankings. Superimposed on the plots is the 0.05 and 0.95 (left) as well as 0.25 and 0.75 (right) quantile regression line as solid blue, the 0.50 median quantile regression line (dashed blue line) and the least squares estimate of the conditional mean function (dashed red line).

Summarising these statistical findings, our ranking imputation approach offers a framework that accounts for the presence of extreme values and more importantly, provides valuable results of the score distribution properties.

4 Cross-Rankings Dependence

The HB common score is used here in the dependence analysis. First, we show the connection and similarities between the considered rankings; then we investigate the influence of age on the ranking scores. Finally, we provide a detailed analysis of the scores relative to the research fields. Note that here we use HB, RP or GS to denote the HB common score, the RP average rank score and the number of GS citations, respectively.

4.1 HB, RP and GS

The distributions of HB and GS scores of researchers are asymmetric, right-skewed and single-peaked, see Figure 4. The heavy tails stretching away from the peaks indicate the presence of many outliers that fall outside of the overall pattern, here associated with extreme values. We have a concentration of data in the left part and a long tail to the right. This represents the vast majority of scientists with lower rankings, with only a few individuals possessing very high rankings. In the RP scores distribution, in contrast, one can identify multiple peaks close together. The structure of the RP average rank score can explain this, as it is calculated from 36 sub-rankings.

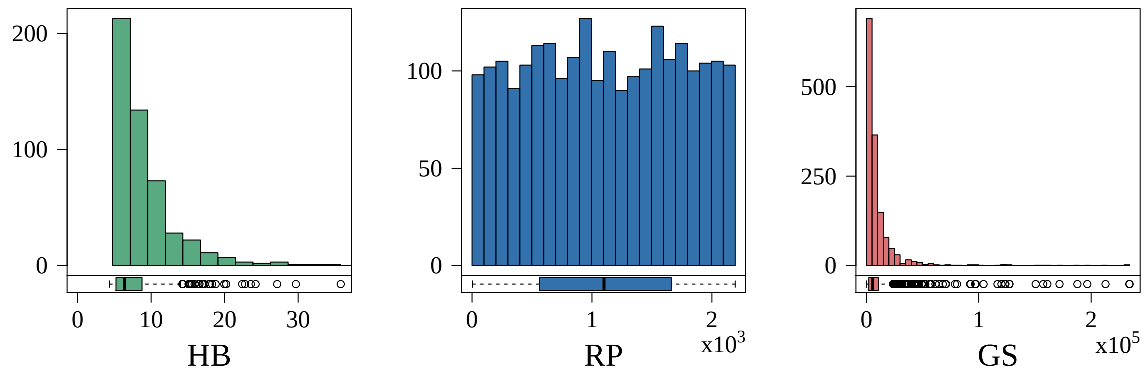

Figure 4: Histogram of HB (500 observations, common score), RP (2,304, total score $\times 10^3$) and GS (1,357, citations $\times 10^5$) rankings for December 2015. ARRhismer

One observes a moderate and positive dependence between the HB, RP and GS scores; please see the parallel coordinates plot, Figure 5. The three quartiles (25%, 50% and

75%) indicate a considerable number of outliers that influence the results. This can be confirmed by removing the extreme scores from HB and GS. The result is shown in Figure 14 in the Appendix.

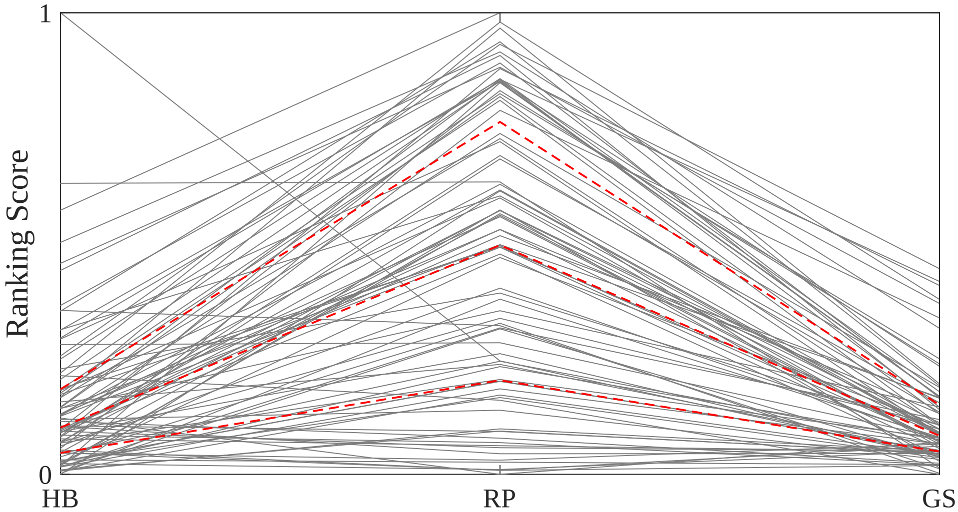

Figure 5: Parallel coordinate plot for three variables (HB, RP and GS) on 84 researchers for December 2015. For convenience, the RP values are reversed. Red lines denote the three quartiles (25%, 50% and 75%). ARRpcpmer

The relationship between HB, RP and GS scores is further analysed for the full data frame consisting of 42 factors in the correlation matrix in Figure 6. Here we use the HB common score and also include the age of researchers as an additional factor. The descriptive statistics is introduced in Table 5 in the Appendix.

The correlation plot reveals that many variables indicate a strong linear relationship. In particular, the correlation between GS citations and other variables varies, mainly moderate to strong. The HB common score shows, in most cases, a moderate correlation. The visible clusters that characterize RP data correspond to the groups of RP sub-rankings. The negative correlation between RP average rank and other variables is due to the difference in scales, as explained in Section 2.2.

One can notice that the RP and GS citations and h-index show a very strong correlation. These pairwise relations are additionally explored through the hexagon plot in Figure

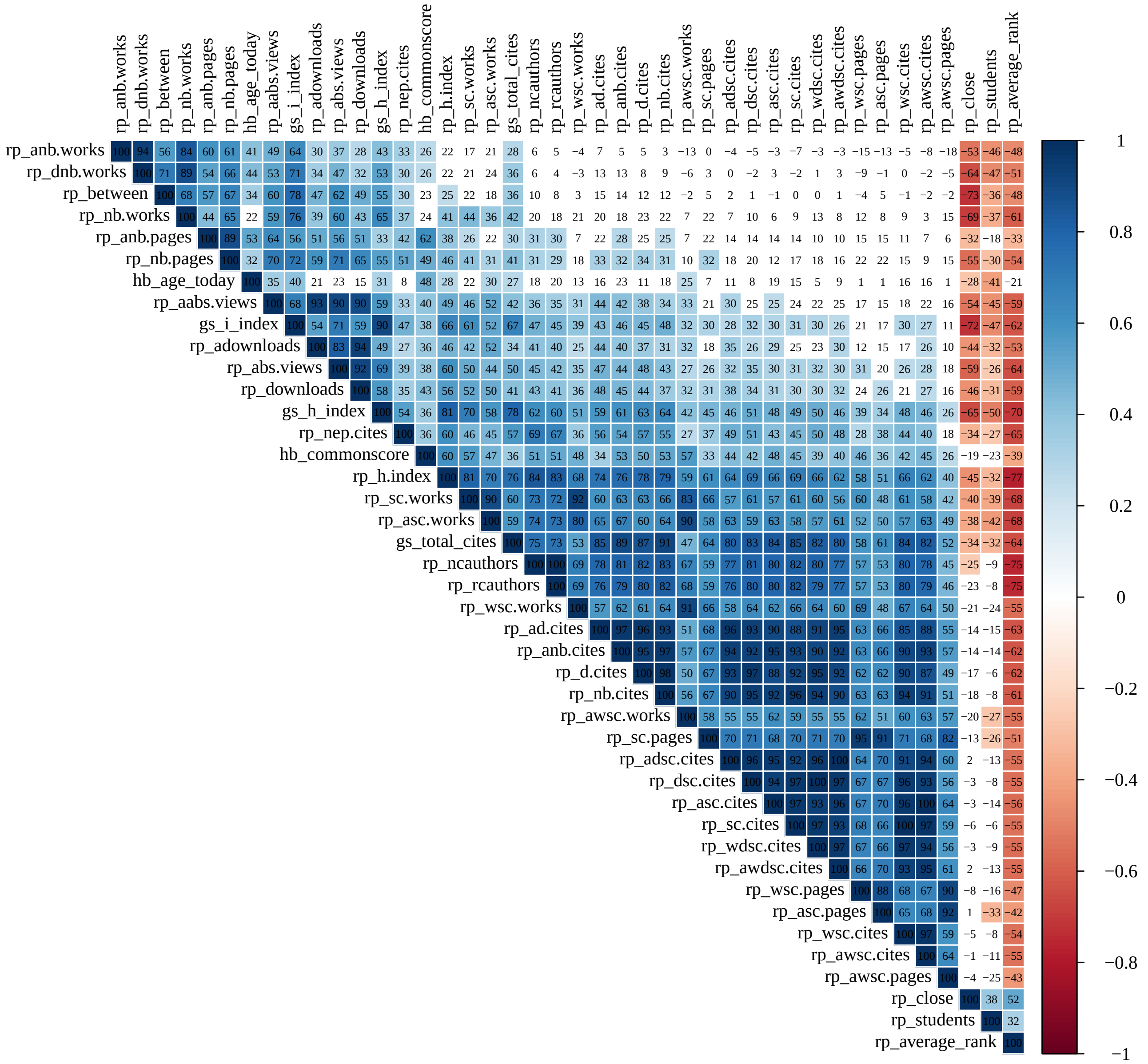

Figure 6: Correlation matrix of 42 factors of HB, RP and GS for 84 researchers in December 2015. The colour depicts the strength of correlation: from positive (blue) to negative (red). ARRcormer

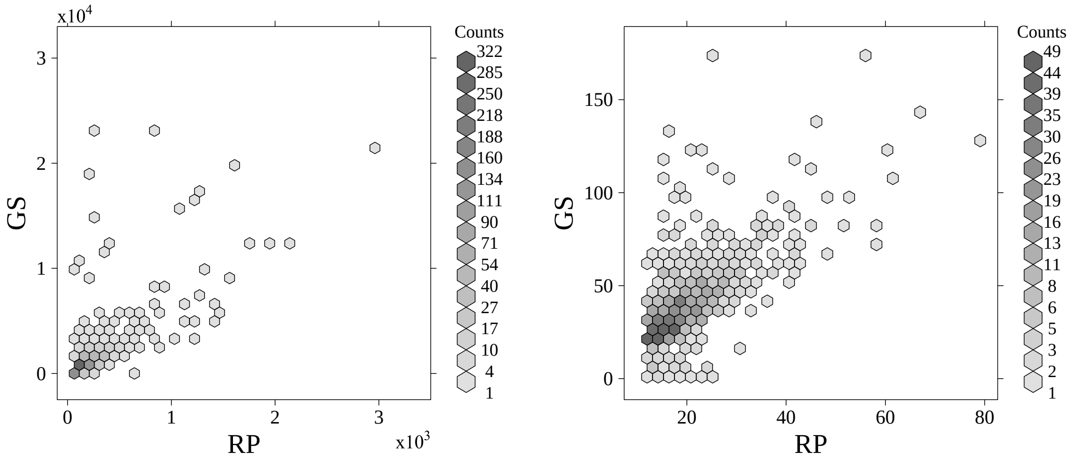

Figure 7: Hexagon plot of RP and GS citations for 1,024 researchers (left) and hexagon plot of RP and GS h-index for 928 researchers (right) in December 2015. Correlation coefficient equals to 0.70 for citations and 0.68 for h-index. ARRhexcit ARRhexhin

7. The Figures indicate a positive linear relationship between the two. However, some outliers that do not follow this trend.

4.2 Influence of Age

Our research question is to study whether age influences the rankings of scientists. As the age data is available for only 458 individuals from HB, we have also reduced the full datasets within RP and GS to the top 458 observations. The scatterplots, hexagon plots and boxplots in Figures 8 – 10 show the relationships between age and ranking scores in a more detailed way.

From Figure 8 one can make several observations. Firstly, that a positive relationship between age and HB ranks exists; for RP it is difficult to identify any pattern of data points. Here it is important to note that some RP rankings are standardized with respect to age, while simultaneously there seems to be a very weak association between age and GS.

For the research aggregate, we divide the ranking scores of scientists into nine groups

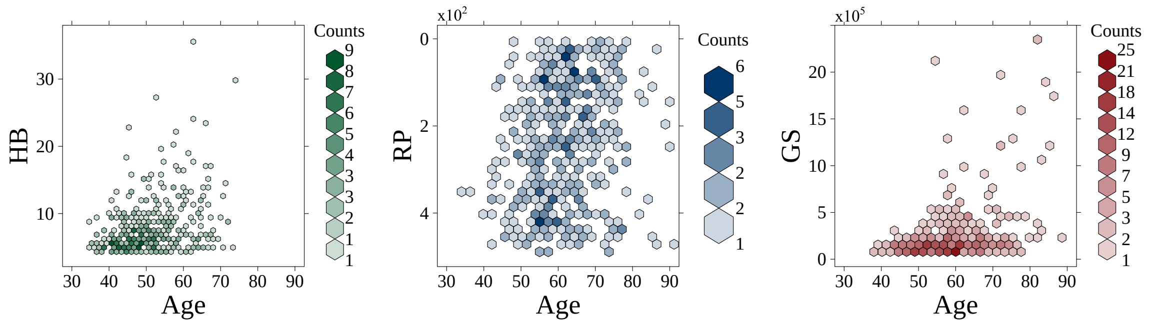

Figure 8: Hexagon plots for age and ranking scores of HB, RP and GS for 458 individuals within each ranking system for December 2015. ARRhexage

with respect to their age with five-year steps, starting with individuals younger than 36 years and concluding with ones older than 70. The overall patterns of response for the age groups are described on the boxplots in Figures 9 – 10.

The notable high box length of ranks from the RP age groups indicates of the high sample variability. On the other hand, the comparatively short boxplots from the GS age groups indicate that GS researchers have only slight difference on the introduced scale. In the same way, the boxplots of HB are comparatively tall. This suggests that 458 of the HB scientists have relatively different ranking scores. Almost all age groups of HB, moreover, indicate the presence of heavy tails in the direction of higher ranks, as, in some cases, the length of the whiskers exceeds the length of the boxes.

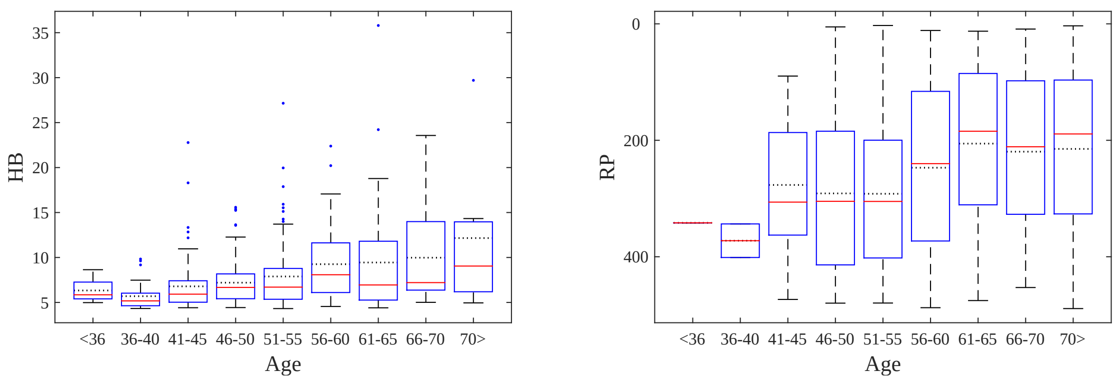

Figure 9: Boxplots for age and ranking scores of HB (left) and RP (right) for 458 individuals within each ranking system for December 2015. The red lines denote the median, whereas the dotted lines introduce the mean. For comparison purposes the RP scale is inverted. ARRboxage

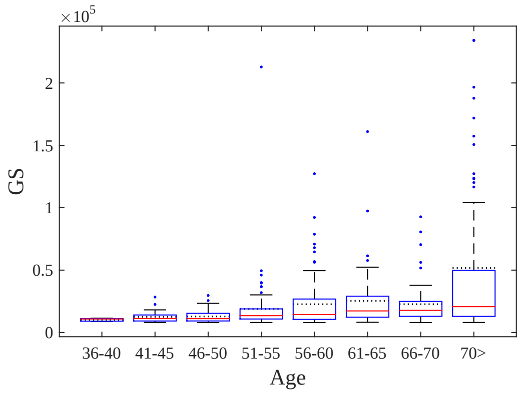

Figure 10: Boxplots for age and ranking scores of GS for Top-458 individuals within each ranking system for December 2015. The red lines denote the median, whereas the dotted lines introduce the mean. ARRboxage

A further analysis shows that ranks of younger researchers are increasing, whereas the middle-aged group has relative consistency or a slight decline and then the next growth trend, amongst scientists of advanced age, could be observed. One possible explanation for this observation could originate from a scientific path in academia. In order to get a position at a university, young researchers are encouraged and motivated to write as many papers as possible and produce other significant outputs, while the middle-aged researchers, who usually have stable positions, concentrate more on teaching, long-term projects and other duties. The slight increase in ranking scores of older individuals could be explained by experience in writing papers, acknowledgement amongst the scientific community, enlarged research networks that they work within and other variables. As a result, this leads to a higher level of work, citations, indexes and number of papers downloaded.

The relative comparison of three academic rankings through the age groups in a four-dimensional plot (HB, RP and GS scores and age) is represented by a mosaic plot in Figure 11. We consider three academic rankings with the 458 researchers from each one. Here HB, RP and GS scores are shown by green, blue and red colours respectively. The width of each column represents the number of individuals within each age group, whereas the coloured dot represents zero.

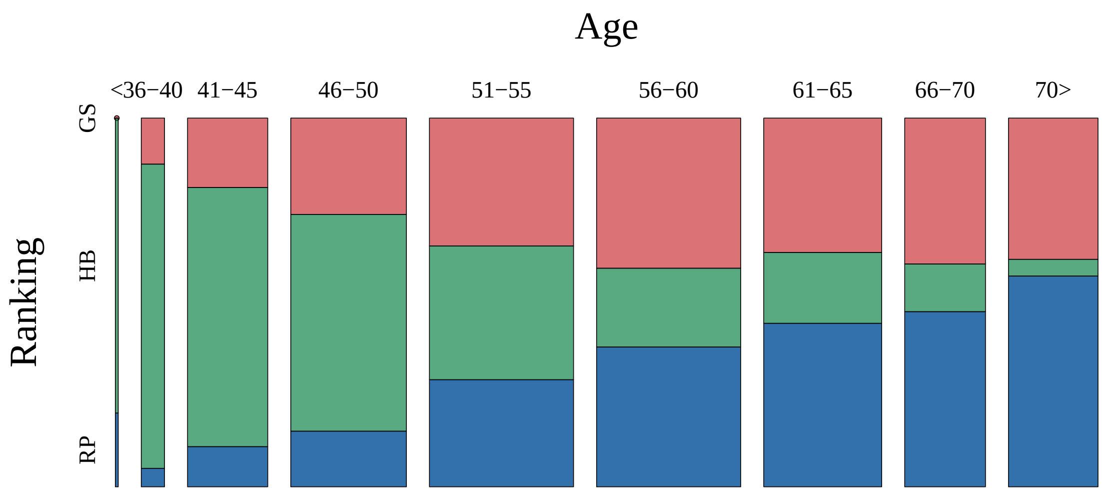

Figure 11: Mosaic plot of HB (green), RP (blue) and GS (red) scores for Top-458 individuals within each ranking system for December 2015. The width of the columns represents the number of persons within each age group. ARRmosagegr

This plot shows that the majority of younger extraordinary researchers belong to the HB group. Amongst the middle-aged ones, the slight domination of GS over the RP system is visible. At the same time, the scientists of advanced age are mostly located in RP and partly in GS areas.

4.3 Research Fields

We were able to enrich our dataset and perform a comparative analysis by adding the research field of scientists provided by HB and GS. From 500 researchers in HB, only 448 individuals have information about subject fields. This constraint forces us to reduce the GS dataset by taking the 448 best ones from Figure 1, thus enabling the comparison. From RP we also select the top 448 individuals, although they are from merged GS and HB data; see Figure 1. As a result, the RP scientists that originally had no information relating to their areas of research receive these from their GS profiles or their HB ranking systems. Therefore, we end up with a dataset that contains 448 scientists within each of the discussed ranking systems with their main research field.

In order to analyse the influence of research area on ranking scores, all researchers were divided into 19 groups of subject fields according to their recognition classification in economic sciences Journal of Economic Literature (JEL), see JEL (accessed 02 Mar 2017). The explanation of the JEL codes is given in Table 7.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	Z	Total
GS	86	3	53	32	43	67	46	13	5	22	0	13	12	0	29	0	13	9	2	448
HB	1	2	49	73	49	39	59	1	6	10	3	48	67	1	24	0	8	4	4	448
RP	72	2	50	41	68	73	42	14	4	26	1	13	2	1	22	1	7	6	3	448

Table 4: Frequency Table for JEL codes and the ranking scores of HB, RP and GS for the top 448 scientists within each ranking system for December 2015.

A distribution of scores of researchers within research areas (JEL codes) and the corresponding ranking systems can be seen on the comparative histograms in Figure 12. The frequency Table 4, generated from our dataset, shows that more than 16% of selected HB researches come from microeconomics (D). They are followed by scientists from the business field (M), financial economics (G), mathematical and quantitative methods (C), and macroeconomics and monetary economics (E), with over 10% within each research area.

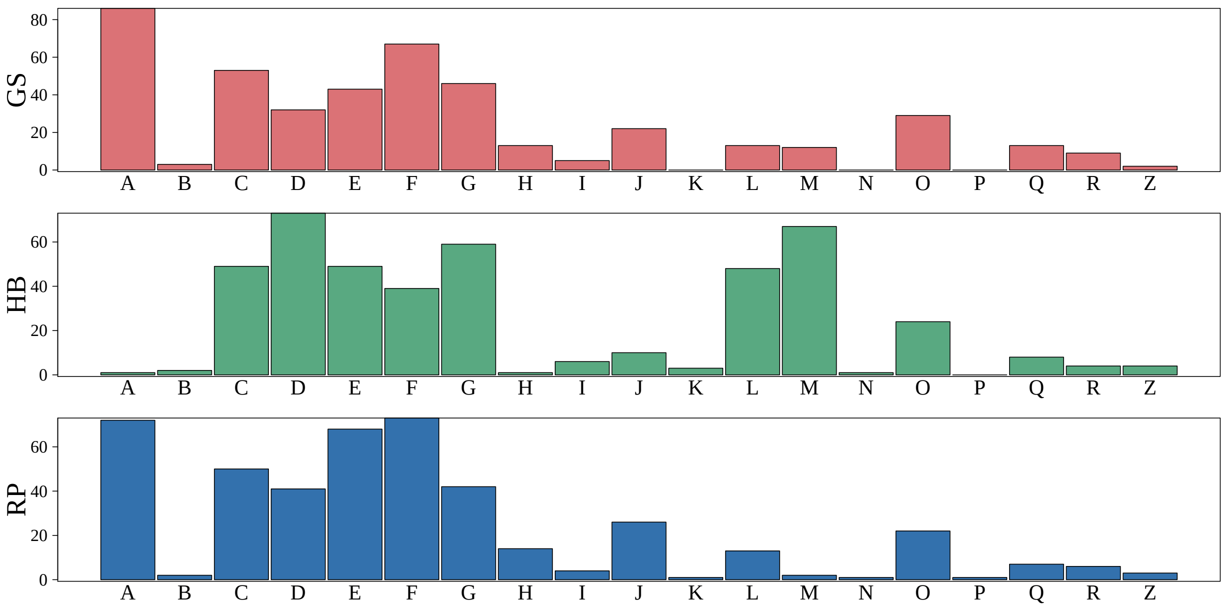

Figure 12: JEL codes and ranking scores of GS (upper/red), HB (middle/green) and RP (lower/blue) for the top 458 scientists within each ranking system for December 2015.

A distinct difference is introduced by RP, where international economics (F), and general economics and teaching (A) hold the leading positions with over 16% for each. Macroeconomics and monetary economics accompany these, along with mathematical and quantitative methods with over 15% and 11% respectively. In the same manner, the dominant research area of GS is presented by general economics and teaching with more than 19% of researchers. Furthermore, international economics produces above 14% of GS, while mathematical and quantitative methods, and financial economics, make up 11% and 10% respectively. However, the mathematical and quantitative methods field is the only research field amongst the ones compared that has over 10% across all three ranking systems.

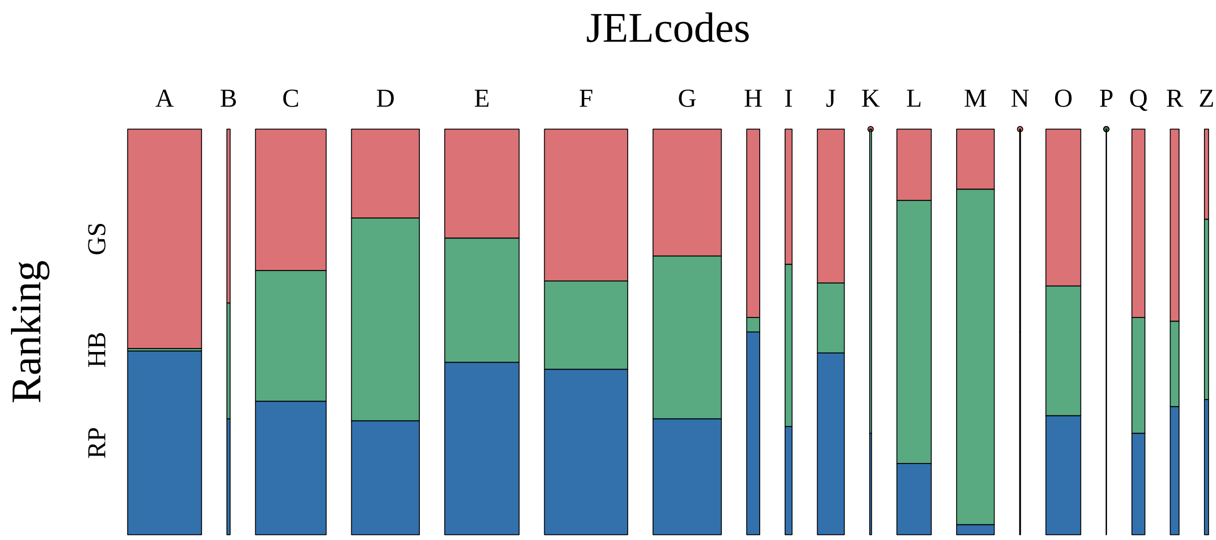

Figure 13: Mosaic plot of JEL codes and ranking scores of GS (upper), HB (middle) and RP (lower) for 458 scientists within each ranking system for December 2015. The width of the columns represents the number of persons within each research area and dots represent zero. ARRmossub

To sum up, we present a mosaic plot in Figure 13 that gives us the advantage of a relative simultaneous comparison of ranking systems through the subject fields in a four-dimensional space. The width of the columns, illustrating the aggregated number of individuals within each research area, brings us to the following important conclusions.

Since the F column is a widest one, the largest number of researchers occupying the leading positions among HB, RP and GS carry out their research in international economics. Fields such as macroeconomics and monetary economics, general economics and teaching, mathematical and quantitative methods, microeconomics and financial economics illustrate a slight little difference. On the other hand, the presence of scientists from economic systems (P), economic history (N), as well as law and economics (K), in the top positions of the discussed ranking systems is rather uncommon.

5 Conclusions

In summary, the comparison of academic ranking scales reveals useful information across ranking systems. Quantile regression successfully imputes the ranking data in the Handelsblatt rankings. The proposed HB common score can be used for the prediction of HB sub-ranking based on available HB data and in an inter-dependence comparison of HB, RP and GS. We have demonstrated that different correlation structures between the underlying sub-rankings exist.

The empirical results show that academic ranking variation is sensitive to age. The rank of younger and advanced-aged scientists increases more significantly than that of middle-aged researchers. Individuals from mathematical and quantitative methods occupy the leading positions across all three of the discussed ranking systems. Individuals from microeconomics, international economics and general economics and teaching present the dominant share within HB, RP and GS, respectively. Finally, the proposed framework successfully completes research profiles of scientists.

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6 Appendix

Code	Research field
A	General Economics and Teaching
B	History of Economic Thought, Methodology, and Heterodox Approaches
C	Mathematical and Quantitative Methods
D	Microeconomics
E	Macroeconomics and Monetary Economics
F	International Economics
G	Financial Economics
H	Public Economics
I	Health, Education, and Welfare
J	Labor and Demographic Economics
K	Law and Economics
L	Industrial Organization
M	Business Administration and Business Economics / Marketing / Accounting / Personnel Economics
N	Economic History
O	Economic Development, Innovation, Technological Change, and Growth
P	Economic Systems
Q	Agricultural and Natural Resource Economics / Environmental and Ecological Economics
R	Urban, Rural, Regional, Real Estate, and Transportation Economics
Y	Miscellaneous Categories
Z	Other Special Topics

Table 7: JEL Classification System

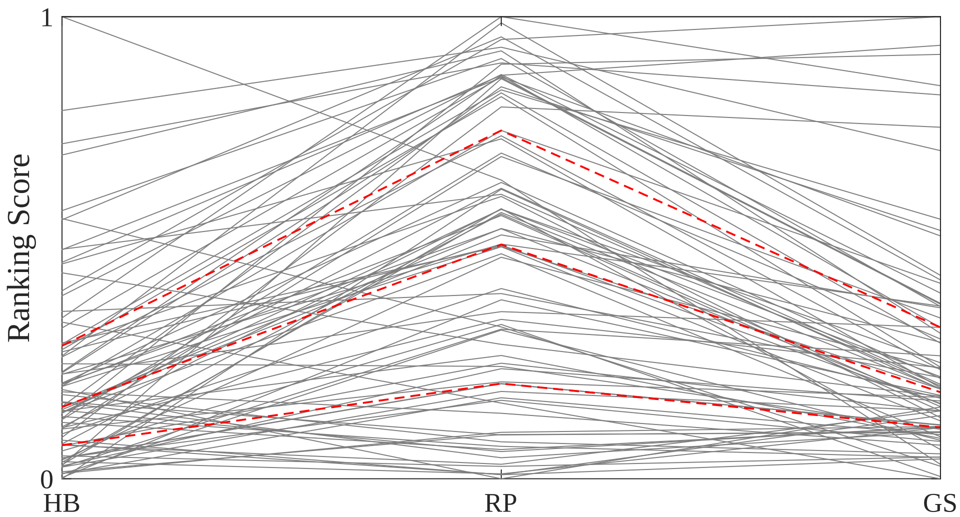

Figure 14: Parallel coordinate plot for three variables (HB, RP and GS) on 82 researchers. Two outliers from HB and GS are removed. Red lines denote the three quartiles (25%, 50% and 75%). RP values are rescaled.

	Count	Mean	St.dev	Median	Min	Max
HB						
Age	458	47.3	9.5	45.0	29.0	75.0
Common Score	500	7.6	3.8	6.4	4.3	35.8
RP						
Average Rank Score	2304	1107.0	631.7	1100.0	2.8	2194.0
Aabs-Views Score	1435	2640.0	2544.7	1861.0	1052.0	36870.0
Abs-Views Score	1529	4447.0	3494.7	3323.0	1860.0	44760.0
Ad-Cites Score	1922	299.6	304.0	200.4	98.9	3378.0
Adownloads Score	1410	738.6	685.9	520.6	287.0	7766.0
Adsc-Cites Score	1874	852.7	880.0	570.2	244.3	10300.0
Anb-Cites Score	1936	1321.0	1432.8	856.7	404.5	16800.0
Anb-Pages Score	1415	877.2	430.8	754.3	463.5	4486.0
Anb-Works Score	1319	109.3	58.6	92.3	55.8	903.7
Asc-Cites Score	1890	13320.0	15007.4	8274.0	3405.0	162100.0
Asc-Pages Score	1680	13610.0	9677.1	10600.0	5414.0	115800.0
Asc-Works Score	1823	1381.0	1010.8	1046.0	555.8	10210.0
Awdsc-Cites Score	1821	180.0	186.9	118.8	48.7	2081.0
Awsc-Cites Score	1835	685.0	785.3	420.1	162.3	8311.0
Awsc-Pages Score	1614	682.8	500.7	524.3	250.8	5334.0
Awsc-Works Score	1718	79.8	63.1	58.4	28.3	592.5
Between Score	1148	10.8	9.3	7.9	3.6	94.7
Close Score	1223	4.6	0.2	4.6	4.0	4.8
D-Cites Score	1889	500.8	494.8	342.8	162.5	5878.0
Dnb-Works Score	1343	128.5	66.1	111.0	68.0	1091.0
Downloads Score	1444	1273.0	992.3	950.0	511.0	10950.0
Dsc-Cites Score	1840	1444.0	1468.3	956.3	418.9	17640.0
H-Index Score	2017	19.4	7.4	17.0	12.0	78.0
Nb-Cites Score	1951	2113.0	2275.9	1385.0	640.0	29620.0
Nb-Pages Score	1521	1211.0	581.4	1046.0	658.0	6722.0
Nb-Works Score	1456	185.8	94.1	161.0	97.0	1288.0
Ncauthors Score	1898	1113.0	844.1	834.0	425.0	7787.0
Nep-Cites Score	1764	82.1	6.9	82.3	69.2	93.9
Rcauthors Score	1897	854.7	633.8	645.2	326.8	5722.0
Sc-Cites Score	1889	21610.0	24319.3	13500.0	5548.0	313000.0
Sc-Pages Score	1762	19410.0	13171.2	15450.0	8056.0	167500.0
Sc-Works Score	1884	2025.0	1402.1	1567.0	851.8	14870.0
Students Score	1093	814.1	575.2	711.2	4.3	2202.0
Wdsc-Cites Score	1787	306.5	313.3	201.6	83.1	3580.0
Wsc-Cites Score	1834	1114.0	1271.3	697.3	265.4	15220.0
Wsc-Pages Score	1681	980.2	678.3	782.2	377.1	7587.0
Wsc-Works Score	1791	116.9	90.2	87.7	43.8	1007.0
GS						
Total Cites	1438	10190.0	19831.2	5332.0	0.0	234200.0
H Index	1438	32.9	20.2	29.0	0.0	177.0
I Index	1438	66.0	69.4	46.0	0.0	814.0

Table 5: Descriptive statistics for 42 factors of HB, RP and GS values. Count means the number of observations, mean is the average of values, St.dev - standard deviation, max and min - maximum and minimum values.

	Count	Mean	St.dev	Median	Min	Max
HB						
<36	4	6.3	1.6	5.8	5.0	8.6
36-40	33	5.7	1.5	5.2	4.3	9.8
41-45	97	6.8	2.8	5.9	4.4	22.8
46-50	117	7.2	2.4	6.7	4.4	15.6
51-55	90	7.9	3.9	6.7	4.3	27.1
56-60	53	9.3	4.0	8.1	4.6	22.4
61-65	39	9.4	6.2	6.9	4.4	35.8
66-70	18	10.0	5.3	7.2	5.0	23.6
>70	7	12.2	8.5	9.0	5.0	29.7
RP						
<36	1	341.8	–	341.8	341.8	341.8
36-40	2	372.4	40.8	372.4	343.6	401.3
41-45	15	276.7	117.8	306.1	89.7	473.3
46-50	30	291.2	140.0	304.8	5.2	479.7
51-55	72	291.8	123.0	305.0	2.8	479.5
56-60	94	247.1	142.5	240.1	11.4	487.5
61-65	90	205.7	137.9	184.4	12.7	475.2
66-70	66	219.5	129.3	211.1	9.0	452.8
>70	88	214.8	147.2	189.1	3.4	489.0
GS						
<36	0	–	–	–	–	–
36-40	5	10240.0	1182.5	10840.0	8758.0	11470.0
41-45	26	12600.0	4745.0	11200.0	8075.0	28400.0
46-50	52	12860.0	5179.4	11070.0	7924.0	29670.0
51-55	86	18780.0	22906.8	13460.0	8012.0	212800.0
56-60	101	22640.0	20020.8	14340.0	7932.0	127300.0
61-65	74	25360.0	22591.8	17290.0	8190.0	161000.0
66-70	55	22680.0	17533.9	17740.0	7931.0	92730.0
>70	59	51730.0	61926.0	20680.0	8022.0	234200.0

Table 6: Descriptive statistics for HB, RP and GS values through age groups. Count means the number of observations, mean is the average of values, St.dev - standard deviation, max and min - maximum and minimum values.

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